True or spurious long memory in European non-EMU currencies

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Abstract

We examine the Croatian Kuna, the Czech Koruna, the Hungarian Forint, the Polish Złoty, the Romanian Leu, and the Swedish Krona whether their Euro exchange rates volatility exhibits true or spurious long memory. Recent research reveals long memory in foreign exchange rate volatility and we confirm this finding for these currency pairs by examining the long memory behavior of squared residuals by means of the V/S test. However, by using the ICSS approach we also find structural breaks in the unconditional variance. Literature suggests that structural breaks might lead to spurious long memory behavior. In a refined test strategy, we distinguish true from spurious long memory for the six exchange rates. Our findings suggest that Czech Koruna and Hungarian Forint only feature spurious long memory, while the rest of the series have both structural breaks and true long memory. Lastly, we demonstrate how to extend existing models to jointly model both properties yielding superior fit and better Value-at-Risk forecasts. The results of our work help to avoid misspecification and provide a better understanding of the properties of the foreign exchange rate volatility.

Keywords: Conditional Variance, Foreign Exchange, GARCH, Spurious Long Memory, Value-at-Risk

JEL: C22, C51, C53, C58

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1. Introduction

Since the collapse of Bretton Woods in 1973, currencies of most economies are floating exchange rates which create the need for currency risk management for cross country transactions. In recent research the main impact factors such as interest rate, inflation, or the trade level of the country have been widely investigated (i.a. Anderson et al., 2003, Taylor & Taylor, 2004, Engel & West, 2005). This study concentrates on volatility-driven foreign exchange forecasts since volatility is a crucial component indicating the stability of a currency and related trade volume (Yang & Gu, 2016). Further, exchange rate volatility has a vital impact on risk management strategies for investors with trades affected to foreign currencies.

The property of long memory of a financial time series refers to long lasting, i.e. slowly decaying, autocorrelation effects in conditional returns or volatility (Baillie, 1996). In time discrete modeling, this effect can be depicted by fractional differencing (Hosking, 1981). Many types of financial time series are reported to attribute long memory in their variance; e.g. individual stocks, stock indices, commodities, and foreign exchange rates (i.a. Baillie et al., 1996, Bollerslev & Mikkelsen, 1996, Chkili et al., 2014).

However, it is proven that sudden structural changes can falsely imitate the behavior of long memory (Granger & Terasvirta, 1999, Diebold & Inoue, 2001, Granger & Hyung, 2004). Mikosch & Starica (1999) examine the case of switching between two volatility processes and show that it leads to spurious long memory in variance. In fact, several studies separately examine either long memory or structural breaks. Engel & Hamilton (1990) find long swings in the currencies of Germany, France, and U.K. against the U.S. Dollar. This finding is supported by other studies, revealing regime switches or structural breaks in foreign exchange rates (Bollen et al., 2000, Rapach & Strauss, 2008). Focusing on long memory, various authors suggest its existence in the returns or the volatility of exchange rates (Cheung, 1993, Bollerslev & Mikkelsen, 1996, Souza et al., 2008). Moreover, some literature copes with spurious long memory in variance (Yalama & Celik, 2013, Charfeddine, 2014, Shi & Ho, 2015, Charfeddine, 2016).

In this work, we focus on countries of the European Union which have not implemented the Euro. Some of them are candidates for joining the European Monetary Union (EMU). This approach limits the data period as early as the general introduction of the Euro in 11 countries in 1999. The examined countries are trading within the European Single Market, hence exchange rates play a vital role for importing and exporting non-EMU countries. Additionally, we also address countries that are candidates for implementation and examine the impact of EU convergence criteria on the properties of exchange rates. Up to now, literature analyzing volatility of Central and Eastern European foreign exchange rates is scarce. Its importance for the individual countries, investors seeking for diversification, and firms—importing and exporting—seems to be neglected, albeit the fact that EUR, USD, JPY, and GBP are much more liquid and do have different characteristics. Murinde & Poshakwale (2001) examine the volatility of Eastern and Central European currencies by means of various volatility models. Kočenda & Valachy (2006) analyze the foreign exchange rates volatility of the Visegard countries. Their findings suggest that changing to a free floating regime increases the volatility compared to a fixed regime. Frömmel (2010) uses a Markov-Regime-Switching volatility model to analyze the currencies of Czech Republic, Hungary, Poland, Romania, and Slovakia. Będowska-Sójka & Kliber (2010) investigate various volatility models and its usage for the Polish Złoty. Horobet et al. (2016) use a Hodrick-Prescott filter to examine volatility for Croatia, Czech Republic, Hungary, Poland, Romania, Russia, Serbia, and Turkey. Klein et al. (2016) show that long memory can be found in the variance of the Polish Złoty against the Euro.

The contribution of this work to existing literature is at least twofold: Firstly, we advance the technique of identifying spurious long memory in variance. Existing tests are only suited to deal with long memory on a return basis. Secondly, we examine the long memory behavior of foreign exchange rates volatility of currencies which are not part of the EMU. Lastly and most importantly, we demonstrate how to jointly model long memory and structural breaks in conditional variance and show its applicability in a Value-at-Risk prediction analysis.

The remainder is structured as follows: Sec. 2 introduces the conditional volatility models. In Sec. 3 the data is described and test results for structural breaks, long memory, and spurious long memory are presented. Sec. 4 analyzes the results of the parameter estimation and Value-at-Risk forecasts of the conditional variance models. Sec. 5 concludes.

2. Methodology

Throughout this paper and especially for the models defined in the subsequent sections, we set for all $t = 1, \ldots, T$:

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, \\ \varepsilon_t &= z_t \sqrt{h_t} \quad \text{with } z_t \sim \mathrm{t}_\nu(0,1) \text{ i.i.d.}, \\ \mu_t &= \mathbb{E}\left[y_t | \mathcal{F}_{t-1}\right], \\ h_t &= \mathbb{V}\left[y_t | \mathcal{F}_{t-1}\right], \end{aligned} \tag{1}$$

where μ_t denotes the conditional mean structure modeled by an Autoregressive Integrated Moving Average (ARIMA) model of the return series $\{y_t\}_{t=0}^T$, h_t denotes the conditional variance at time t, and $\mathcal{F}_{t-1}$ refers to the sigma-algebra generated by the past of the time series up to time $t-1$. The random variable z_t stems from a centered and standardized Student's t-distribution with ν degrees-of-freedom as in Bollerslev (1987).

For the following models, the definition given in (1) holds while we further specify the conditional variance structure. We introduce volatility models to capture the effect of long memory and structural breaks separately and then jointly. As we only present three alternative long memory models with variance shift, it should be noted that several other models exist (Ben Nasr et al., 2010, Klç, 2011, Belkhouja & Boutahary, 2011, Shi & Ho, 2015).[1]

[1] For reasons of robustness, we also test a Markov-Regime-Switching variant of FIGARCH. The results remain the same and are available upon request.

2.1. Generalized Autoregressive Conditional Heteroskedasticity

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model Engle (1982), Bollerslev (1986) expresses the conditional variance h_t as dependent on squared residuals ε_t^2 with lags of order q and the predecessors of h_t up to order p. Throughout this paper we set the orders of p and q to one. Hence, the GARCH(1,1) can be given by

$$h_t = \omega_0 + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1},$$

with the non-negativity conditions $\omega > 0$, $\alpha, \beta \geq 0$ and the stationarity condition $\alpha + \beta < 1$. If $\alpha + \beta = 1$, the resulting process is referred to as Integrated GARCH (IGARCH), which is not weakly stationary (Nelson, 1990).

2.2. Fractionally Integrated GARCH

To depict the property of long memory in volatility, one has to choose a very high order of lags and hence, an excessive amount of parameters if using a GARCH(p,q)-framework. In order to be more parsimonious, the alternative is the Fractionally Integrated (FI-)GARCH by Baillie et al. (1996). The FIGARCH(p,d,q) adds the fractional integration (or long memory) parameter d with $0 \leq d \leq 1$. The FIGARCH(1,d,1) is given as

$$\begin{aligned} h_t &= \omega_0 + \left(1 - \beta L - (1 - \alpha L)(1 - L)^d\right) \varepsilon_t^2 + \beta h_{t-1} \\ &= \frac{\omega_0}{1 - \beta} + \sum_{i=1}^{\infty} \lambda_i \varepsilon_{t-i}^2, \end{aligned} \tag{2}$$

where L denotes the lag-operator. All parameters must be non-negative and the restriction $0 \leq \beta + \alpha \leq d \leq 1$ must hold. The second line of (2) is the ARCH(∞) representation with λ_i calculated from the FIGARCH parameters α, d, and β as shown in Bollerslev &

Mikkelsen (1996).[2] Furthermore, $\sum_{i=1}^{\infty} \lambda_i < 1$ is required for stationarity. Interestingly, if $d = 0$ FIGARCH turns to a plain GARCH and if $d = 1$ the special case of an IGARCH, with infinite persistence of shocks, is matched.

2.3. ICSS-FIGARCH

In order to adjust FIGARCH to different regimes, a sequential approach combining the volatility models with a preliminary structural break test is implemented. Mansur et al. (2007) use the Iterated Cumulative Sum of Squares (ICSS, Inclan & Tiao, 1994) method together with a bivariate GARCH for foreign exchange spot and forward rates. We alter their procedure by using the ICSS variation of Sansó et al. (2004), which appears more robust towards conditional heteroskedasticity. Firstly, we run the ICSS test and detect B structural break points. Secondly, we augment FIGARCH with dummy variables D_i and corresponding parameters ω_i for all $i = 1, \ldots, B$. Hence, (2) is altered to:

$$h_t = \frac{\omega_t}{1-\beta} + \sum_{i=1}^{\infty} \lambda_i \varepsilon_{t-i}^2,$$

$$\omega_t = \omega_0 + \sum_{i=1}^{B} \omega_i D_i.$$

By doing so, the augmented ICSS-FIGARCH variant depicts the possibility to shift the unconditional variance depending on a given regime. In addition to the parameter restrictions of FIGARCH, the non-negativity is maintained as long as $\omega_i > -\omega_0$ for all $i = 1, \ldots, B$.

2.4. Spline-FIGARCH

A second model variation of the FIGARCH with a time-dependent unconditional variance is the Spline-FIGARCH. Engle & Rangel (2008) present the Spline-GARCH, which we

[2] We apply the Fast Fractional Differencing algorithm suggested by Klein & Walther (2017) to obtain the $\sum_{i=1}^{\infty} \lambda_i \varepsilon_{t-i}^2$ for FIGARCH and its variants. For each series we set the truncation lag to 5 000.

transfer to long memory FIGARCH. The Spline-FIGARCH(1,d,1,k) can be expressed in the following way:

$$h_t = \tau_t g_t, \tag{3}$$

$$g_t = (1-\beta) + \sum_{i=1}^{\infty} \lambda_i \frac{\varepsilon_{t-i}^2}{\tau_{t-i}}, \tag{4}$$

$$\tau_t = c \exp\left(\omega_0 \frac{t}{T} + \sum_{i=1}^{k} \omega_i \max\left(\frac{t-t_i}{T}, 0\right)^2\right). \tag{5}$$

The process τ_t describes the low-frequency variance. Due to the exponential character, no additional restrictions for non-negativity are required. To determine the number of knots k, Engle & Rangel (2008) suggest to use an information criterion. We use the Bayesian Information Criterion (BIC). The choice of knots divides the time series in $k+1$ parts of the same length with the change points at $t_1, \ldots, t_k$. Additionally, we suggest to let the ICSS test define the number of knots $k = B + 1$ and the specific break points $t_1, \ldots, t_B$.

2.5. Adaptive-FIGARCH

The Adaptive-(A-)FIGARCH suggested by Baillie & Morana (2009) uses the Fourier flexible function form of Gallant (1984) to vary the unconditional variance over time. The A-FIGARCH(1,d,1,k) reads as follows:

$$h_t = \tau_t g_t, \tag{6}$$

$$g_t = (1-\beta) + \sum_{i=1}^{\infty} \lambda_i \frac{\varepsilon_{t-i}^2}{\tau_{t-i}}, \tag{7}$$

$$\tau_t = c \exp\left(\omega_0 + \sum_{j=1}^{k} \left[\gamma_j \sin\left(2\pi j t/T\right) + \delta_j \cos\left(2\pi j t/T\right)\right]\right). \tag{8}$$

All parameter specifications of FIGARCH have to hold for A-FIGARCH as well. In order to maintain non-negativity in the time-varying unconditional part we use the exponential specification of Engle & Rangel (2008). Baillie & Morana (2009) mention that $k = 1$ or 2 already lead to good results. However, as with the Spline-GARCH we determine the number k by minimizing BIC.

It should be noted that neither ICSS-, Spline-, nor A-FIGARCH are covariance stationary due to their time-varying variance level. In regards of predictions, we extrapolate the last regime for all $s \in \mathbb{N}$ by $\mathbb{E}\left[\omega_{T+s}|\mathcal{F}_T\right] = \hat{\omega}_T$ and $\mathbb{E}\left[\tau_{T+s}|\mathcal{F}_T\right] = \hat{\tau}_T$, respectively.

3. Data

3.1. Descriptive Analysis

Our research focuses on exchange rates of six European countries that are not members of the EMU. Namely, we examine the Czech Koruna (CZK), the Croatian Kuna (HRK), the Hungarian Forint (HUF), the Polish Złoty (PLN), the Romanian Leu (RON), and the Swedish Krona (SEK) against the Euro. We retrieve the daily exchange rate data from Thomson Reuters DataStream for the period from January 4, 1999 to December 31, 2015. We calculate the log returns $r_t = 100 \cdot \log \frac{P_t}{P_{t-1}}$ for all $t = 1, \ldots, T$ prices P_t. For every time series, we obtain 4433 daily observations. For the out-of-sample analysis, we use the period from January 2, 2006 to December 31, 2015, resulting in a total number of $M = 2608$ out-of-sample observations for each series.

The descriptive statistics and the preliminary tests are given in Table 1. The Czech Koruna (EUR/CZK) and the Swedish Krona (EUR/SEK) feature a negative mean over the whole sample, while the remaining series have a positive mean in returns. The daily standard deviation spans from 0.28 (EUR/HRK) to 0.67 (EUR/PLN). The descriptive statistics of the skewness and kurtosis as well as the Jarque-Bera test suggest that the time series are not normally distributed. We use the method of Ljung & Box (1978) to test for autocorrelation in returns for a lags of 12 and 64 days. The test statistics are all above their corresponding

	EUR/CZK	EUR/HRK	EUR/HUF	EUR/PLN	EUR/RON	EUR/SEK
			Descriptive statistics			
T	4433	4433	4433	4433	4433	4433
Mean	-0.0059	0.0007	0.0051	0.0010	0.0279	-0.0007
St. Dev.	0.4318	0.2830	0.5775	0.6697	0.5762	0.4477
Minimum	-4.1602	-2.1411	-3.5606	-4.1552	-8.6126	-3.0062
Maximum	4.5096	2.6302	6.4628	5.5072	12.3031	2.9802
Skewness	0.3549	0.1378	1.1579	0.3858	2.4769	0.1080
Kurtosis	12.3991	9.3796	14.9728	8.1061	74.6041	7.0024
			Preliminary tests			
JB	16383.87***	7518.14***	27425.05***	4916.56***	950238.72***	2961.48***
LB (12)	50.7814***	432.7458***	26.8082***	45.2680***	87.2662***	45.2205***
LB (64)	161.6614***	569.2836***	93.4884***	133.3865***	200.7880***	135.5586***
ARCH (12)	53.6483***	79.6279***	79.8534***	69.5852***	54.4931***	71.5187***
ARCH (64)	119.1151***	229.2110***	143.4520***	143.6567***	190.5064***	128.4646***
ADF	-72.5947***	-91.7756***	-67.3124***	-70.3353***	-63.6339***	-69.3006***
KPSS	0.0392	0.0114	0.0099	0.0253	0.2067**	0.0395

Table 1: Descriptive statistics and preliminary tests for the log-return data from January 4, 1999 to December 31, 2015. JB is the Jarque-Bera test, LB is the Ljung-Box test for auto-correlation in returns, ARCH is the Engle test for ARCH effects, ADF is the augmented Dickey-Fuller test, and KPSS is the Kwiatkowski, Phillips, Schmidt and Shin test. The null hypothesis of each test is rejected at 5% (**) and 1% (***).

critical values and reject the hypothesis of no autocorrelation. Moreover, we apply the Lagrange Multiplier test of Engle (1982) to check for autocorrelation in squared returns as a proxy for the variance at the same lags. We find all test statistics to be significant at a level of 1%. Finally, the test for unit roots in the returns series with the augmented Dickey-Fuller test and the KPSS test are carried out. Except for EUR/RON, we assume all series to be stationary by the results of these tests. For the Romanian Leu, the augmented Dickey-Fuller test rejects the null hypothesis of no unit root, however, the KPSS test rejects the null hypothesis of non-stationarity.

3.2. Test for Structural Breaks

We apply the ICSS variant of Sansó et al. (2004) on the six exchange rate returns. The identified structural breaks in each series are given in Table 2. Fig. 1 illustrates these breaks. Most of them can be explained by exogenous shocks or other, country-specific factors.

Most importantly, all series share a similar pattern which is explained by the global contagion of the sub-prime crisis towards the worldwide financial crisis. In 2008, four out of six series feature a break from a low volatility regime or period to a high volatility period.

EUR/CZK	EUR/HRK	EUR/HUF	EUR/PLN	EUR/RON	EUR/SEK
07/07/2004	20/11/2003	04/02/2008	19/02/2002	05/05/2009	22/10/2002
14/08/2007	11/10/2012	15/06/2009	24/07/2006		13/10/2008
09/09/2008		06/08/2012	02/09/2008		04/09/2009
24/04/2009			11/08/2009		
07/11/2013			17/09/2012		

Table 2: Structural breaks in the time series from January 4th, 1999–December 31st, 2015.

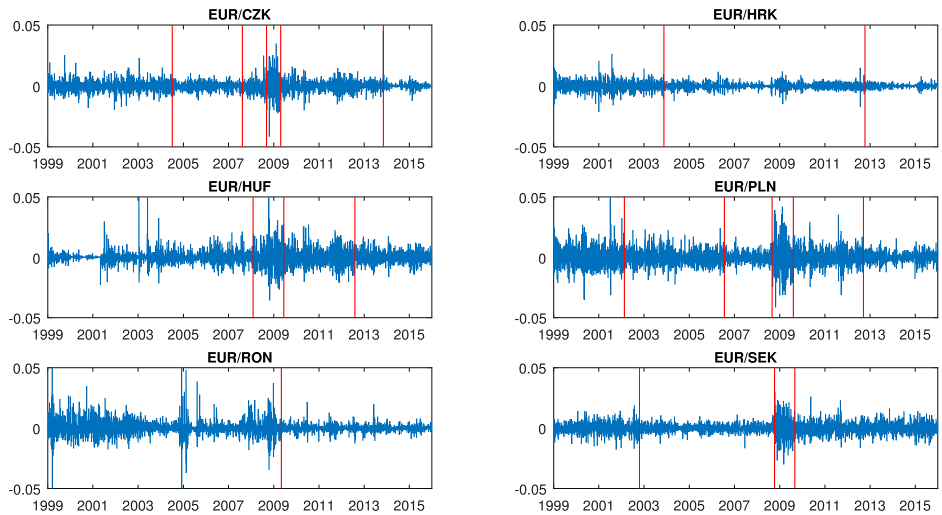

Figure 1: Structural volatility breaks (red vertical lines) from ICSS in the time series from January 1, 1999 to December 31, 2015.

Around this time, Lehman Brothers went bankrupt even though it was considered 'too big to fail'. The impact of the worldwide market turbulence due to Lehman's default is observable in all series and lasts up to 12 months. After this highly volatile period, a period with lower variance follows.

Another important break is observable for EUR/CZK after Czech Republic left the Central European Free Trade Agreement (CEFTA) and joined the EU in 2004. For the EUR/HUF and EUR/PLN exchange rate, no break after joining the EU is identified which might be due to the already low volatility during this time. Central bank interventions are observable for the Czech Koruna in November 2013 with a break towards a low volatility regime. On November 7, 2013, the Czech National Bank announced to asymmetrically intervene and floor the CZK/EUR at 27. The last break in the EUR/PLN pair might be caused by the Polish central bank determining further conditions for joining the EMU. For the Swedish

Krona, a break from a high towards a low volatility regime is observed in November 2002. The monetary introduction of the Euro might be a possible explanation.

Despite the wakes of the European debt crisis, ongoing political conflicts within the EU, and a mediocre economic situation without a long-lasting positive trend, the results suggest that all exchange rates are in a stable low volatility regime by the end of the sample period. Volatility levels are comparable to the period before the sub-prime crisis. Hence, we observe an easing in exchange rate volatility over all currency pairs focused on–some of them caused by central bank interventions in order to comply with EU convergence criteria.

3.3. Test for Spurious Long Memory

We begin our analysis by testing the squared returns for long memory using the V/S test (Giraitis et al., 2003, 2005).[3] Since the test statistic incorporates an estimator for the autocovariance with Bartlett weights (as in Lo, 1991), a truncation lag q needs to be chosen. We select 20, 60, and 120, to capture long run autocovariance.

Our results show that all exchange rates exhibit long memory in squared returns. The test statistics are given in the left panel of Table 3. For the chosen lag $q = 20$ all test statistics reject the null hypothesis of no long memory at a level of significance of 1%. For a lag $q = 60$ only the exchange rate EUR/HRK, EUR/HUF, and EUR/SEK remain at the same level. Still significant, the test statistics for EUR/CZK and EUR/RON feature p-values below 5% and EUR/PLN below 10%. Lastly, the test statistics for $q = 120$ suggest that EUR/HRK and EUR/HUF have a very long persistence and evidence to support the long memory in variance can be found for EUR/CZK, EUR/RON, and EUR/SEK at level of significance of 10%. However, the test statistic for EUR/PLN is too low to reject the null hypothesis. We summarize that the EUR/PLN has less persistent memory in variance than the other exchange rates. As it appears that the long memory effect is present, GARCH models incorporating this effect will yield a better fit.

[3] Giraitis et al. (2003) demonstrate that the V/S test has more power than commonly chosen tests identifying long memory of squared returns.

	squared returns			squared filtered residuals		
	$M_{20}(y_t^2)$	$M_{60}(y_t^2)$	$M_{120}(y_t^2)$	$M_{20}(y_t^2)$	$M_{60}(y_t^2)$	$M_{120}(y_t^2)$
EUR/CZK	0.4981***	0.2473**	0.1524*	0.0775	0.0732	0.0705
EUR/HRK	1.0381***	0.5682***	0.3885***	0.1874**	0.1426	0.1163
EUR/HUF	0.8735***	0.4990***	0.3266***	0.0947	0.0979	0.1004
EUR/PLN	0.3121***	0.1618*	0.1053	0.2403**	0.1960**	0.1487
EUR/RON	0.1625*	0.1249	0.1057	0.3068***	0.2393**	0.2178**
EUR/SEK	0.6823***	0.2957***	0.1776*	0.4160***	0.3528***	0.2783***

Table 3: Test statistics for the long memory test with the V/S test for squared returns and squared filtered residuals. We use 20, 60, and 120 lags with Bartlett weights for the sample auto-correlation in the V/S test. The time series spans from January 1st 1999–December 31st, 2015. Rejections of the null hypothesis of no long memory is rejected at 10% (*), 5% (**), and 1% (***).

After testing the six exchange rate returns for long memory and structural breaks separately, we test for spurious long memory by alteration of the idea of Charfeddine (2016). By minimizing the BIC, we choose the best fitting Markov Regime Switching (MRS, Hamilton, 1994) model for each series and repeat the V/S test on filtered residuals. The results are then compared to the test statistics of the squared residuals.

The results of the V/S test are given in the right panel of Table 3 and can be compared to the statistics in the left panel.[4] The V/S test on the filtered squared residuals of the MRS models show that EUR/CZK and EUR/HUF lose the persistence of shocks in volatility. For EUR/HRK the degree of persistence is reduced and only the statistic at $q = 20$ is significant. Interestingly, EUR/RON unveils long memory after filtering for structural break. For the remaining EUR/PLN and EUR/SEK time series the results are stable and still reject the hypothesis of no long memory in variance at $q = 20$ and 60.

Hence, we assume that for the Czech Koruna and the Hungarian Forint the long memory property is a spurious phenomenon. The other four pairs: Croatian Kuna, Polish Zloty, Romanian Leu, and Swedish Korona feature 'true' long memory. For these four pairs, structural breaks are an additional property and do not interfere with the shock persistence.

[4] By minimizing the BIC of the MRS models, we identify three regimes for EUR/CZK, EUR/HRK, EUR/PLN, and EUR/SEK and four regimes for EUR/HUF and EUR/RON.

4. Results & Discussion

4.1. Parameter Estimations

The results from the Maximum Likelihood estimation for the models presented in Sec. 2 are given in Table 4 to 9. In order to identify possible ARIMA structures, we use the Box et al. (2008) procedure and minimize the BIC. We find the following structures: ARIMA(0,0,1) for EUR/CZK and EUR/HRK, ARIMA(1,0,1) for EUR/HUF and EUR/SEK, ARIMA(0,0,0) for EUR/RON[5], and ARIMA(1,0,1) for EUR/PLN with an intercept. We find all ARIMA parameter estimates to be significantly different from zero over all time series. Moreover, all estimates for the Student's t-distribution parameter ν are significant and confirm our preliminary results from Sec. 3.

Firstly, we focus on the EUR/CZK pair. For the simple GARCH model, we observe a very high persistence ($\alpha + \beta \approx 1$). The persistence is also present in the FIGARCH, where the fractional difference parameter d is close to one; estimates for both processes depict the IGARCH effect. Augmenting FIGARCH with the possibility of time-varying unconditional variance does not change the persistence by much. Notably, all models estimate a d of close to one, yielding non weakly stationary processes (Davidson, 2004). This could indicate that non-stationarity is interpreted as spurious long memory, which is in line with the findings from the test for spurious long memory. The best model by means of fit (LL) and goodness-of-fit (BIC) is ICSS-FIGARCH. It is obvious that all models with regime-varying ω_i outperform GARCH and FIGARCH.

For the EUR/HRK pair, we find a high persistence in the GARCH parameters. When incorporating structural breaks, however, the fractional difference parameter d ranges between 0.4425 and 0.5834. We thus conclude that the structural breaks explain some of the persistence and spurious long memory in the Croatian Kuna and the remaining long range

[5] The KPSS test in Section 3 rejects the null-hypothesis of stationarity for EUR/RON, albeit the augmented Dickey-Fuller test rejects non-stationarity. Therefore, we also tested ARIMA(0,1,1) for reasons of robustness. However, the results remain qualitatively the same and are available from the authors upon request.

	GARCH	FIGARCH	ICSS-FIGARCH	Spline-FIGARCH	ICSS-Spline-FIGARCH	A-FIGARCH
θ_1	-0.1014***	-0.1127***	-0.1142***	-0.1151***	-0.1153***	-0.1152***
ω_0	0.0003	0.0002***	0.0053***	5.1550***	7.8583*	1.9384
c				0.1353***	0.1353**	0.0002***
ω_1 / γ_1			-0.0020***	-7.7017***	-15.6885	-3.6892***
ω_2 / δ_1			0.0028***		12.0294	-2.0057***
ω_3 / γ_2			0.0554***		94.2331	-2.8724***
ω_4 / δ_2			-0.0004***		-52.5903	-0.5279***
ω_5			-0.0050***		-102.7319	
ω_6					-99.8699	
α	0.0734***	0.0057e-5***	0.0053e-5***	0.0000	0.0000	0.0021***
d		1.0000***	1.0000***	1.0000***	1.0000***	0.9957***
β	0.9266***	0.9233***	0.8815***	0.9031***	0.9022***	0.9200***
ν	5.2128***	5.3738***	4.1997***	4.8603***	4.6721***	4.9209***
LL	-1619	-1593	**-1556**	-1574	-1567	-1577
BIC	3279	3237	**3204**	3215	3243	3246
LB(12)	7.0921	7.1061	6.9638	7.6194	6.7537	6.7030
ARCH(12)	26.0043**	15.5552	22.6833**	20.0454*	18.3603	13.1086

Table 4: Estimation results for the log-returns of EUR/CZK. The time series spans January 4, 1999 to December 31, 2015. Rejections of the null hypothesis that parameters are zero is rejected at 10% (*), 5% (**), and 1% (***). LL is the Log-Likelihood, BIC is the Bayesian Information Criterion, LB is the Ljung-Box statistic, and ARCH is the Engle test. The values in bold face indicate the best fit (LL) and goodness-of-fit (BIC).

dependence can be interpreted as 'true' long memory. This is illustrated by the fact that A-FIGARCH yields the best in-sample fit (LL), but FIGARCH has the better goodness-of-fit (BIC).

For EUR/HUF returns, the picture is somewhat similar to the EUR/CZK results. We find a high persistence of shocks in variance in GARCH, yielding covariance-nonstationary processes. The FIGARCH variants show a high level of d. The joint modeling with time-varying unconditional variance lowers the level of d, however. Hence, structural breaks explain some part of the persistence. Spline-FIGARCH (LL and BIC) outperforms its competitors.

For EUR/PLN, we observe an IGARCH effect in GARCH ($\alpha + \beta = 0.9956$), yet the fractional differencing parameter d in FIGARCH is 0.4278. These findings correspond to earlier results of Klein et al. (2016). Moreover, parameter estimates differ little across the FIGARCH variants. The log likelihood of FIGARCH is slightly lower than of ICSS-FIGARCH, which features the highest LL; yielding the lowest BIC for FIGARCH. In conclusion, EUR/PLN shows evidence that observable structural breaks in variance do not alter the persistence of shocks and we observe 'true' long memory.

	GARCH	FIGARCH	ICSS-FIGARCH	Spline-FIGARCH	ICSS-Spline-FIGARCH	A-FIGARCH
θ_1	-0.2879***	-0.2924***	-0.2903***	-0.2916***	-0.2925***	-0.2906***
ω_0	0.0002**	0.0000	0.0070***	13.2125	12.0423*	0.9248
c				0.0202	0.0159	0.0026***
ω_1 / γ_1			-0.0070***	-43.3682	-40.2576***	1.0441***
ω_2 / δ_1			-0.0070***	85.0391*	56.0461***	-0.0275***
ω_3 / γ_2				-103.7337***	-123.0113	0.6655***
ω_4 / δ_2						0.4311***
ω_5						-0.7879***
ω_6						-0.3084***
α	0.0697***	0.2184**	0.2083*	0.2599	0.2677	0.2787***
d		0.5632***	0.5834***	0.4801	0.4647***	0.4425***
β	0.9303***	0.5406**	0.5450*	0.4719	0.4887	0.4404***
ν	5.1063***	5.3268***	5.1605***	5.1238***	5.4540***	4.9921***
LL	427	527	531	543	537	**549**
BIC	-813	**-1004**	-995	-1002	-990	-989
LB(12)	10.9226	9.3643	8.9111	9.1782	9.1341	9.6730
ARCH(12)	36.1880***	27.8651***	27.9299***	15.3263	16.3730	16.6793

Table 5: Estimation results for the log-returns of EUR/HRK. The time series spans January 4, 1999 to December 31, 2015. Rejections of the null hypothesis that parameters are zero is rejected at 10% (*), 5% (**), and 1% (***). LL is the Log-Likelihood, BIC is the Bayesian Information Criterion, LB is the Ljung-Box statistic, and ARCH is the Engle test. The values in bold face indicate the best fit (LL) and goodness-of-fit (BIC).

	GARCH	FIGARCH	ICSS-FIGARCH	Spline-FIGARCH	ICSS-Spline-FIGARCH	A-FIGARCH
ϕ_1	0.6774***	0.6840***	0.6816***	0.6772***	0.6794***	0.6855***
θ_1	-0.7377***	-0.7356***	-0.7325***	-0.7277***	-0.7297***	-0.7353***
ω_0	0.0001	0.0004e-5***	0.0007e-8***	-29.0834***	-17.4132***	2.7685*
c				0.0000	0.0100e-5***	0.0017***
ω_1 / γ_1			0.0350***	76.6842***	41.9940***	-2.7026***
ω_2 / δ_1			0.0203***	-104.2919***	-207.8643***	-0.5642***
ω_3			0.0091***	18.0279	160.6183***	
ω_4					16.6025*	
α	0.0789***	0.0374***	0.0514***	0.1394***	0.1425***	0.1126***
d		0.9252***	0.8970***	0.7211***	0.7150***	0.7748***
β	0.9211***	0.8814***	0.8469***	0.7217***	0.7256***	0.7701***
ν	4.8331***	5.2037***	4.5224***	4.2291***	4.2958***	4.5225***
LL	-2536	-2496	-2464	**-2451**	-2453	-2466
BIC	5121	5051	5011	**4995**	5006	5016
LB(12)	5.8659	2.4800	1.6633	1.5648	1.5736	1.7703
ARCH(12)	6.8973	4.3396	3.8189	3.7776	3.9634	4.1030

Table 6: Estimation results for the log-returns of EUR/HUF. The time series spans January 4, 1999 to December 31, 2015. Rejections of the null hypothesis that parameters are zero is rejected at 10% (*), 5% (**), and 1% (***). LL is the Log-Likelihood, BIC is the Bayesian Information Criterion, LB is the Ljung-Box statistic, and ARCH is the Engle test. The values in bold face indicate the best fit (LL) and goodness-of-fit (BIC).

	GARCH	FIGARCH	ICSS-FIGARCH	Spline-FIGARCH	ICSS-Spline-FIGARCH	A-FIGARCH
μ	-0.0091**	-0.0088***	-0.0089***	-0.0087**	-0.0087***	-0.0089***
ϕ_1	0.4972***	0.5150***	0.5146***	0.5133***	0.5141***	0.5128***
θ_1	-0.5858***	-0.5973***	-0.5970***	-0.5956***	-0.5963***	-0.5952***
ω_0	0.0034***	0.0076e-5***	0.0231***	-0.6966	-0.7474	0.4298***
c				0.0810**	0.0785*	0.3690
ω_1 / γ_1			-0.0119***	-1.3978	-0.9351	-0.2546***
ω_2 / δ_1			-0.0227***		-0.6228	
ω_3 / γ_2			0.1771***		-0.2439	
ω_4 / δ_2			-0.0157***		0.0502***	
ω_5			-0.0231***		0.2895	
ω_6					0.9830	
α	0.0765***	0.2193***	0.2081***	0.2256***	0.2268***	0.2227***
d		0.4278***	0.4398***	0.3932***	0.3921***	0.4302***
β	0.9191***	0.5514***	0.5436***	0.5252***	0.5253***	0.5591***
ν	6.4985***	7.1328***	6.5806***	7.2984***	7.3136***	7.3804***
LL	-3783	-3746	**-3738**	-3744	-3744	-3750
BIC	7625	**7559**	7585	7572	7614	7592
LB(12)	11.8964	10.3321	10.5076	10.4906	10.4992	9.9165
ARCH(12)	32.4187***	23.2598**	23.2443**	23.3908**	23.3600**	23.8556**

Table 7: Estimation results for the log-returns of EUR/PLN. The time series spans January 4, 1999 to December 31, 2015. Rejections of the null hypothesis that parameters are zero is rejected at 10% (*), 5% (**), and 1% (***). LL is the Log-Likelihood, BIC is the Bayesian Information Criterion, LB is the Ljung-Box statistic, and ARCH is the Engle test. The values in bold face indicate the best fit (LL) and goodness-of-fit (BIC).

Regarding the estimates of the EUR/RON currency pair given in Table 8, we observe similar results as for EUR/PLN. GARCH yields IGARCH parameters. In contrast, the FIGARCH variants yield parameters that depict a long memory process as well as significant break point specific regimes of unconditional variance. The Spline-FIGARCH yields the best fit with respect to LL and BIC.

Lastly, the EUR/SEK yields more consistent results given in Table 9. All parameter estimates produce covariance stationary processes. Notably, the d estimates for FIGARCH are much higher than for the FIGARCH variants that allow for structural breaks. Thus, again we observe that the structural breaks explain the persistence of shocks to some extend. Given the similarity of parameter estimates, the log likelihood of the models is similar as well, yielding the highest LL for ICSS-FIGARCH and the lowest BIC for FIGARCH.

In summary, we detect spurious long memory for the EUR/CZK currency pair. The parameter estimates produce covariance non-stationary processes and strong evidence against 'true' long memory. For the remaining currency pairs, we observe a varying degree of long memory which is still present after allowing for structural breaks in the unconditional variance

	GARCH	FIGARCH	ICSS-FIGARCH	Spline-FIGARCH	ICSS-Spline-FIGARCH	A-FIGARCH
ω_0	0.0023***	0.0023***	0.0106***	22.2991***	-1.3433	1.2115
c				0.1353	0.1353	0.0141***
ω_1 / γ_1			-0.0078***	-81.5096***	-4.5005	1.0844***
ω_2 / δ_1				127.0363***	22.6599	0.9445***
ω_2 / δ_1				-62.3219***		0.4436
ω_2 / δ_1				27.2316		-0.2964
α	0.1130***	0.1997***	0.1506***	0.1607	0.2393	0.1838**
d		0.6005**	0.6988	0.6785***	0.5214	0.6325
β	0.8870***	0.6021	0.6483	0.5864*	0.5335	0.5800
ν	3.8303***	4.1943***	4.0325***	3.7108***	4.1254***	3.8418***
LL	-1973	-1904	-1899	**-1874**	-1893	-1882
BIC	3979	3851	3848	**3831**	3853	3848
LB(12)	21.8453**	33.7401***	33.3927***	38.9400***	36.3266***	39.6009***
ARCH(12)	32.4940***	24.9937**	28.6488***	22.7300**	20.0545*	21.0955**

Table 8: Estimation results for the log-returns of EUR/RON. The time series spans January 4, 1999 to December 31, 2015. Rejections of the null hypothesis that parameters are zero is rejected at 10% (*), 5% (**), and 1% (***). LL is the Log-Likelihood, BIC is the Bayesian Information Criterion, LB is the Ljung-Box statistic, and ARCH is the Engle test. The values in bold face indicate the best fit (LL) and goodness-of-fit (BIC).

	GARCH	FIGARCH	ICSS-FIGARCH	Spline-FIGARCH	ICSS-Spline-FIGARCH	A-FIGARCH
ϕ_1	0.7299***	0.7365***	0.7395***	0.7429***	0.7432***	0.7426***
θ_1	-0.7823***	-0.7881***	-0.7913***	-0.7940***	-0.7941***	-0.7938***
ω_0	0.0011***	0.0009***	0.0503e-5***	-2.1204	7.1027**	0.9715***
c				0.3520e-5***	0.0252	0.0090***
ω_1 / γ_1			-0.0503e-5***	2.1523	-29.1497***	-0.2907***
ω_2 / δ_1			0.0969***	0.0251	43.6182***	0.2745***
ω_3			0.0048***	2.3888*	-24.7183**	
ω_4					2.3238	
α	0.0504***	0.0223***	0.2447***	0.2744***	0.2858***	0.2749***
d		0.9554***	0.5105***	0.4511***	0.4284***	0.4502***
β	0.9448***	0.9287***	0.7073***	0.6745***	0.6621***	0.6741***
ν	6.8200***	6.5416***	6.5537***	7.0378***	6.9935***	6.9814***
LL	-2096	-2088	**-2078**	-2083	-2081	-2082
BIC	4242	**4235**	4241	4242	4263	4249
LB(12)	16.5456	15.1923	13.0404	14.6999	14.5815	14.2694
ARCH(12)	15.2597	8.9117	11.5088	11.6440	12.4159	11.7208

Table 9: Estimation results for the log-returns of EUR/SEK. The time series spans January 4, 1999 to December 31, 2015. Rejections of the null hypothesis that parameters are zero is rejected at 10% (*), 5% (**), and 1% (***). LL is the Log-Likelihood, BIC is the Bayesian Information Criterion, LB is the Ljung-Box statistic, and ARCH is the Engle test. The values in bold face indicate the best fit (LL) and goodness-of-fit (BIC).

level. As expected, the fit benefits from modeling a time-varying unconditional variance. This performance is evoked by the existence of different regimes visualized and easily observable in Fig. 1. The FIGARCH variants with time-varying unconditional variance also result in the best goodness-of-fit, especially for those time series where we observed spurious long memory in advance.

4.2. Value-at-Risk Forecast Evaluation

In order to evaluate the models regarding their applicability for risk management, we forecast the Value-at-Risk (VaR) with each model. The VaR is a loss in market value of a portfolio. The probability that it occurs or is exceeded over a given time horizon is equal to a prior defined tolerance level a. It is still one of the most popular risk measures used by financial institutions (Jorion, 2006, Campbell, 2006). We define VaR as a conditional quantile (VaR_y) of the forecasted return distribution:

$$P\left(y_t \leq VaR_y\right) = P\left(y_t \leq \mu_t + \sqrt{h_t} F_{\mathrm{t}}^{-1}\left(a, \nu\right)\right) = a, \tag{9}$$

where $F_{\mathrm{t}}^{-1}(a, \nu)$ is a quantile of the conditional Student's t-distribution related to the probability of a and the degrees-of-freedom ν. For the out-of-sample period, we conduct a one-day ahead VaR forecast. To compare the results of the models, we use three different back tests. The unconditional coverage test by Kupiec (1995, KUP) checks whether the number of VaR violations is correct. Pérignon & Smith (2008) suggest to extend the KUP test to jointly evaluate more than one quantile. We use their multivariate unconditional coverage test (MUC) at 1% and 5%. Finally, we incorporate the duration based procedure by Candelon et al. (2011, GMM) to test the independence of individual VaR violations.[6] We present the results of the back tests for each model and different currencies in long and short position in Table A.10-A.15.

[6] For an overview of VaR tests with comparison of power see e.g. Piontek (2010, 2013).

We observe that no model is the best in all cases. However, the FIGARCH class models are rejected in fewer cases than the simple GARCH model. The results show that models incorporating both, long memory and structural breaks are usually not rejected for the Czech Koruna and Swedish Krona and rarely rejected for Romanian Leu and Polish Złoty. The VaR of the Croation Kuna is best depicted by the A-FIGARCH, especially the long trading position. The Hungarian Forint seems challenging for the models used in this study and only the ICSS-FIGARCH is able to pass the KUP test for the short trading position. If we compare the number of tests rejected, the ICSS-FIGARCH is least rejected (18 out of 60 tests). The second best choice are Spline- and ICSS-Spline-FIGARCH (19) followed by A-FIGARCH (20) and FIGARCH (22). The worst result is achieved by the simple GARCH specification with almost half of the tests rejected (27). Hence, we advice practitioners to use a model which depicts the joint effect of long memory and structural breaks.

5. Conclusions

In this study, we examine the Polish Złoty, the Romanian Leu, the Swedish Krona, the Hungarian Forint, the Czech Koruna, and the Croatian Kuna whether their Euro exchange rates volatility exhibit true or spurious long memory. Firstly, we examine the exchange rates on structural breaks of their variance and find multiple break points in all series. The financial crisis caused a synchronized shock to the variance in all examined series. It is also found that central bank interventions cause structural breaks. In regard to these findings, literature suggests that structural breaks can lead to spurious long memory behavior. Secondly, we employ a refined test strategy to discriminate true from spurious long memory. In a first step, we test all time series on long memory in variance using the V/S test and find all series to exhibit long memory to a certain extend. In a second step, the long memory property is tested again, after filtering all series with a Markov Regime Switching model. The results show that neither the Czech Koruna nor the Hungarian Forint exhibit evidence of true long memory. Finally, we extend existing volatility models to jointly model long memory and structural breaks. The analysis of the estimated parameters from different volatility models is in line with the findings of our test strategy. Moreover, we analyze the Value-at-Risk forecast accuracy of the different models by means of three VaR back tests. Models which depict long memory and structural breaks yield both the best in-sample and forecasted Value-at-Risk performance. The results of our work help to avoid misspecification and provide a better understanding of the properties of the foreign exchange volatility.

Future research could analyze the causes and drivers of market fluctuations of the foreign exchange rates. Recent GARCH specifications (Engle et al., 2013) allow to incorporate monthly or quarterly macroeconomic data (e.g. interest and inflation rates) as explanatory variables in daily volatility models via the Mixed Data Sampling approach.

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Appendix A.

	pos.	KUP 1%	KUP 5%	MUC	GMM 1%	GMM 5%	rej.
EUR/CZK	long	0.8305	0.4444	0.6228	0.9039	0.9672	0
	short	0.6782	0.6910	0.8912	0.8441	0.9710	0
EUR/HRK	long	0.0281**	0.0000***	0.0002***	0.9906	0.9934	3
	short	0.0111**	0.0000***	0.0000***	0.8260	0.6079	3
EUR/HUF	long	0.0044***	0.0479**	0.0001***	0.9995	0.3977	3
	short	0.0000***	0.0000***	0.0000***	0.9907	0.9674	3
EUR/PLN	long	0.0178**	0.0000***	0.0000***	0.1389	0.0314**	4
	short	0.5362	0.0107**	0.0325**	0.9985	0.0000***	3
EUR/RON	long	0.0178**	0.0012***	0.0029***	0.9978	0.4196	3
	short	0.8305	0.0237**	0.0514*	0.4297	0.0559*	3
EUR/SEK	long	0.8305	0.8859	0.9443	0.8749	0.9647	0
	short	0.4512	0.0128**	0.0424**	0.9896	0.9640	2

Table A.10: Value-at-Risk back testing results for GARCH in the period January 2, 2006 to December 31, 2015. The corresponding p-values for each test are given. Rejection of the null hypothesis is displayed by *, **, *** for 10%, 5% and 1% significance level. Here, pos. indicates the trading position and rej. is the number of tests rejected for a model.

	pos.	KUP 1%	KUP 5%	MUC	GMM 1%	GMM 5%	rej.
EUR/CZK	long	0.5362	0.6811	0.6251	0.9961	0.0000***	1
	short	0.5362	0.7590	0.8251	0.9616	0.2223	0
EUR/HRK	long	0.0023***	0.0000***	0.0000***	0.9747	0.9459	3
	short	0.0002***	0.0000***	0.0000***	0.8586	0.0394**	4
EUR/HUF	long	0.0019***	0.0316**	0.0000***	0.9779	0.5045	3
	short	0.0002***	0.0000***	0.0000***	0.9921	0.9382	3
EUR/PLN	long	0.0921*	0.0383**	0.0790*	0.8567	1.0000	3
	short	0.5362	0.1019	0.0934*	0.7872	0.9220	1
EUR/RON	long	0.2121	0.0906*	0.2024	0.9972	0.8243	1
	short	0.7088	0.8288	0.8514	0.8443	0.0950*	1
EUR/SEK	long	0.6782	0.8997	0.9159	0.4942	0.9741	0
	short	0.3471	0.0128**	0.0447**	0.7358	0.9640	2

Table A.11: Value-at-Risk back testing results for FIGARCH in the period January 2, 2006 to December 31, 2015. The corresponding p-values for each test are given. Rejection of the null hypothesis is displayed by *, **, *** for 10%, 5% and 1% significance level. Here, pos. indicates the trading position and rej. is the number of tests rejected for a model.

	pos.	KUP 1%	KUP 5%	MUC	GMM 1%	GMM 5%	rej.
EUR/CZK	long	0.5362	0.7474	0.6693	0.9702	0.6280	0
	short	0.4512	0.6172	0.7403	0.9373	0.0777*	1
EUR/HRK	long	0.0281**	0.0000***	0.0000***	0.8813	0.9352	3
	short	0.0040***	0.0000***	0.0000***	0.1356	0.9076	3
EUR/HUF	long	0.0000***	0.0141**	0.0000***	0.9295	0.5938	3
	short	0.4512	0.1019	0.2623	0.0405**	0.9683	1
EUR/PLN	long	0.3008	0.2578	0.4385	0.8455	0.5530	0
	short	0.3471	0.0028***	0.0106**	0.6286	0.6238	2
EUR/RON	long	0.0178**	0.0006***	0.0017***	0.9927	1.0000	3
	short	0.9874	0.1100	0.2048	0.9259	0.0088***	1
EUR/SEK	long	0.4093	0.7590	0.7105	0.7300	0.9619	0
	short	0.5724	0.0583*	0.1600	0.9744	0.9494	1

Table A.12: Value-at-Risk back testing results for ICSS-FIGARCH in the period January 2, 2006 to December 31, 2015. The corresponding p-values for each test are given. Rejection of the null hypothesis is displayed by *, **, *** for 10%, 5% and 1% significance level. Here, pos. indicates the trading position and rej. is the number of tests rejected for a model.

	pos.	KUP 1%	KUP 5%	MUC	GMM 1%	GMM 5%	rej.
EUR/CZK	long	0.6782	0.4444	0.5331	0.9934	0.9342	0
	short	0.7088	0.4457	0.5426	0.9999	0.9993	0
EUR/HRK	long	0.0013***	0.0000***	0.0000***	0.8941	0.9674	3
	short	0.0007***	0.0000***	0.0000***	0.0000***	0.9733	4
EUR/HUF	long	0.0000***	0.0000***	0.0000***	0.7259	0.9982	3
	short	0.0564*	0.8159	0.0874*	0.6970	0.8831	2
EUR/PLN	long	0.0178**	0.0107**	0.0138**	0.9696	0.7183	3
	short	0.9874	0.0851*	0.1608	0.9350	0.9933	1
EUR/RON	long	0.9874	0.8159	0.9650	0.9796	0.9900	0
	short	0.1365	0.0316**	0.0832**	0.8173	0.1346	2
EUR/SEK	long	0.3008	0.7590	0.5791	0.9754	0.9771	0
	short	0.9874	0.0583*	0.1102	0.9741	0.9058	1

Table A.13: Value-at-Risk back testing results for Spline-FIGARCH in the period January 2, 2006 to December 31, 2015. The corresponding p-values for each test are given. Rejection of the null hypothesis is displayed by *, **, *** for 10%, 5% and 1% significance level. Here, pos. indicates the trading position and rej. is the number of tests rejected for a model.

	pos.	KUP 1%	KUP 5%	MUC	GMM 1%	GMM 5%	rej.
EUR/CZK	long	0.3008	0.1972	0.0980*	0.9719	0.8069	1
	short	0.8305	0.3439	0.6226	0.9582	0.9975	0
EUR/HRK	long	0.0001***	0.0000***	0.0000***	0.9852	0.9883	3
	short	0.0007***	0.0000***	0.0000***	0.0000***	0.8223	4
EUR/HUF	long	0.0000***	0.0000***	0.0000***	0.7259	0.9906	3
	short	0.0178**	0.0740*	0.0408**	0.9428	0.9854	3
EUR/PLN	long	0.0091***	0.0740*	0.0245**	0.9634	0.7717	3
	short	0.4512	0.0479**	0.1402	0.8478	0.9985	1
EUR/RON	long	0.0921*	0.1100	0.1502	0.9985	0.7135	1
	short	0.9874	0.8997	0.9911	0.3147	0.3165	0
EUR/CZK	long	0.3008	0.2578	0.4385	0.9815	0.9893	0
	short	0.5724	0.1213	0.2988	0.8074	0.9350	0

Table A.14: Value-at-Risk back testing results for ICSS-Spline-FIGARCH in the period January 2, 2006 to December 31, 2015. The corresponding p-values for each test are given. Rejection of the null hypothesis is displayed by *, **, *** for 10%, 5% and 1% significance level. Here, pos. indicates the trading position and rej. is the number of tests rejected for a model.

	pos.	KUP 1%	KUP 5%	MUC	GMM 1%	GMM 5%	rej.
EUR/CZK	long	0.3008	0.6172	0.3445	0.9805	0.9464	0
	short	0.7088	0.7590	0.8111	0.8313	0.4255	0
EUR/HRK	long	0.8305	0.3469	0.5086	0.8656	0.9602	0
	short	0.4512	0.0028***	0.0096***	0.0821*	0.8932	3
EUR/HUF	long	0.0091***	0.0003***	0.0000***	0.9749	0.3383	3
	short	0.0000***	0.0000***	0.0000***	0.9156	0.9078	3
EUR/PLN	long	0.0564*	0.0024***	0.0079***	0.9811	0.9919	3
	short	0.1432	0.3938	0.0955*	0.7273	0.9907	1
EUR/RON	long	0.0008***	0.0000***	0.0000***	0.8824	0.9166	3
	short	0.0921*	0.0107**	0.0312**	0.8699	0.0047***	4
EUR/SEK	long	0.2121	0.5022	0.4535	0.6297	0.9779	0
	short	0.5724	0.2291	0.4848	0.9965	0.9356	0

Table A.15: Value-at-Risk back testing results for Adaptive-FIGARCH in the period January 2, 2006 to December 31, 2015. The corresponding p-values for each test are given. Rejection of the null hypothesis is displayed by *, **, *** for 10%, 5% and 1% significance level. Here, pos. indicates the trading position and rej. is the number of tests rejected for a model.

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